DEEP CNN BASED DECISION SUPPORT SYSTEM FOR DETECTION AND SEVERITY CLASSIFICATION IN DIABETIC RETINAL IMAGES

S.Hemavathi[1],Dr.S.Padmapriya[2]

PG Student,Department of CSE,A.V.C college of engineering,Mannampandal,India
hemavathi2396@gmail.com

Head of the Department,CSE,A.V.C college of engineering,Mannampandal,India
padmapriya.anad14@gmail.com

ABSTRACT - *Diabetic retinopathy (DR) is one of the leading cause of blindness, but the classification of DR requires experienced ophthalmologist to distinguish the presence of various small features, which is time-consuming and difficult. Deep convolutional neural networks (CNN) – the most popular kind of deep learning algorithms - enjoyed great success in the field of image analysis and recognition. In this project, a novel deep convolutional neural network, which performs the early-stage detection by identifying all microaneurysms (MAs), the first signs of DR, along with correctly assigning labels to retinal fundus images which are graded into negative categories. The input of this project is an retinal image and it is given to the preprocessing stage for removal of noise. The preprocessed image is applied to the seed detection process with the help of seed growing algorithm. Then the extracted seed image is given to the Deep CNN classifier. The Deep CNN performs augmentation and gives a multi-category classification of retinopathy grading from high-resolution image.*

1.INTRODUCTION

Diabetic retinopathy(DR), one of the most common retinal diseases, is a common complication of diabetes and one of the major causes of blindness in humans. Since the disease is a progressive process, medical experts suggest that diabetic patients need to be detected not less than twice a year in order to timely diagnose signs of illness. In the current clini- cal diagnosis, the detection mainly relies on the ophthalmologist examining the color fundus image and then evaluates the patient's condition. This detection is arduous and time-consuming, which results in more error. Furthermore, due to the large number of diabetic patients and the lack of medical resources in some areas, many patients with DR can not timely diagnosed and treated, thus lose the best treatment opportunities and eventually lead to irreversible visual loss, as well as even the consequences of blindness. Especially for those patients in early phase, if DR can be found and treated immedi- ately, the deteriorated process can be well controlled and delayed. At the same time, the effect of manual interpretation is extremely dependent on the clinician's experience. Misdiagnosis often occurs due to the lack of experience of medical doctors. IFor diagnosis and monitoring of various eye diseases, ophthalmologists use fundus images which will be taken as input to our system as well. Fundus photography takes into account the retina, fovea, macula and optic disc and creates an image for it. Fundus images are digitized data given by fundus camera that can be used for detection of diabetic retinopathy.

2.LITERATURE SURVEY

Smitha & kodoth proposed the severity level detection of diabetic retinopathy using extreme learning machine classifier. The risk of diabetic retinopathy increases with age and small eye blood vessel are damaged as a result. Information about blood vessels and optic disk detection can be identified for the level of severity and also helpful for diagnosing the disease. The OD is differentiated as the largest circular high contrast area. The blood vessels also appear with high contrast, but the sizes of these areas are much smaller than the area of the OD. Texture features are not only able to isolate normal and abnormal lesions. The median filter is a nonlinear filtering technique that is used to remove noise from images for improving the results of later processing. The median filter may be applied prior to segmentation to reduce the amount of noise in the images to calculate the median pixel values. The feature set needed for the classification phase are extracted using the gray level co-occurrence matrix. Extreme learning machine comprises of a single hidden layer and it belongs to the family of feed forward neural network based supervised classifier. The advantage of this paper is Extreme learning machine need less training time compared to back propagation network and the extraction of optic disk is done in an proper manner. The disadvantage of this paper is it will lead to the problem of easy overfittting and the local minima issue can also be arised. Wang et.al., focused the Diabetic Retinopathy Stage Classification using Convolutional Neural Networks. In deep learning, the convolutional neural network uses a complex architecture composed of stacked layers in which it is particularly well-adapted to classify the images. For multi-class classification, this architecture is robust and sensitive to each feature present in the images. In the stage of preprocessing the retinal image is to be resized for the dimension of 448 * 448 pixels. To improve the accuracy we used three consecutive convolutional layers followed by a max pool layer to make our model deeper. The deep learning feature extraction method from large set of training images autonomously without any need of explicit mention. Transfer learning means to use a model that has already been trained on other images. In the stage of preprocessing Images with the same radii were used to retrain the Inception network at a time. The advantage of this paper is the inception v3 solves over fitting attributed to a large number of parameters and large need of computation resources for an increasing size of network. The disadvantage of this paper it will be more complex for large data sets and it is acceptable for small data sets. Prasad et.al., present an an automated diabetic retinopathy classification system using bayesian logistic regression classifier. Contrast Limited adaptive histogram equalization technique is used to highlight the MA and other lesions in a better way. For detecting the edges, Laplacian of Gaussian (LoG) function is used to mark the edges as it highlights the regions where the intensity changes rapidly and as the image was already smoothened using image enhancing techniques. The statistical features of the image like mean, third moment,entropy, standard deviation, homogeneity, gray level co occurrencematrix (GLCM) and kurtosis are extracted. Textural attributes are extracted from the grey scale images and optimal features are selected. Bayesian Logistic Regression (BLR) classifier is used for classifying the images as DR-Present and DR-absent for the publicly available database. The advantage of this paper is optimal features are selected for classification of diabetic retinopathy and the level of disease formed. The disadvantage of this paper is Imbalance in proportion between very few MA pixels and a large number of background pixels. Hemanth et.al., describe an methodology for diagnosing the diabetic retinopathy from retinal images using modified hop field neural network. The combination of morphological operations and filtering techniques improves the quality of the image . The next step in the automated system is extracting the relevant features from each image and minimizing the complexity of the ANN based classification process . Six textural features (mean, standard deviation, entropy, energy, variance and contrast) are taken from each of the images from both the categories to aid in accurate classification of the images .The advantage of this paper is weight values and output values can be adjusted simultaneously. The disadvantage of this paper is feature selection is not only possible to classify DR. Yadav et.al., proposed the detection of diabetic retinopathy using feed forward neural network. Detection of diabetic retinopathy disease level emphasizes on determination of two types of diabetic retinopathy: Hemorrhages and Exudates. These are extracted using fundus images of patients and is applied to the stage of preprocessing. The median filter is used to remove the noise from the image. For the extraction of optic disk contours are detected to encompass yellow regions and they are they labelled according to their size. For the extraction of blood vessel A gradient image is made by subtracting the kernel image and the original green channel image. For the detection of exudates Dilation of the morphological operation is used on two separate images using one kernel each. Stochastic Gradient descent is applied to get the accuracy of each image. The advantage of this paper is Dot Hemorrhages will be identified accurately. The disadvantage of this paper is One kernel to be used for dilation it will produce a blur image.

3.ARCHITECTURE DIAGRAM

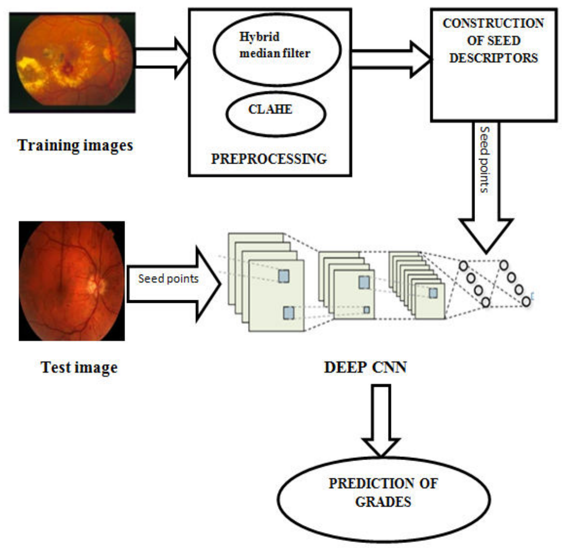

Figure - 3.1 System Architecture

Lot of retinal images are stored in the database for training purpose. The test image is given to the preprocessing stage for the removal of noise. Then the filtered image is given to the Seed growing algorithm for the purpose of constructing the seed points. The seed points will help to detect the affected area .The disparity mapped area is given to the Deep CNN classifier. The deep CNN classify the grades according to the affected part of that image.

4.METHODOLOGY : There are three main stages: preprocessing, construction of seed descriptor, Deep CNN classification

4.1PREPROCESSING

The main aim of preprocessing is an improvement of the image data that suppress the unwanted distortions or enhances some of the image features important for further processing. The input Retinal image is given from the database to the preprocess stage. Hybrid median filter is used to remove the noise distortion in an image. . The hybrid median filter takes two medians: in an "X" and in a "+" centered on the pixel. The output is the median of these two medians and the original pixel value. One advantage of the hybrid median filter is due to its adaptive nature, which allows the filter to perform better than the standard median filter on fast-moving picture information of small spatial extent.

ALGORITHM

1. Place a cross-window over element;
2. Pick up elements;
3. Order elements;
4. Take the middle element;
5. Place a +-window over element;
6. Pick up elements;
7. Order elements;
8. Take the middle element;
9. Pick up result in point 4, 8 and element itself;
10. Order elements;
11. Take the middle element.

4.2 CONSTRUCTION OF SEED DESCRIPTOR

seed growing algorithm to estimate the scene flow in a binocular-video setup. A basic principle of the seed growing methods is that correspondences are found in a small neighborhood around an initial set of seed corre spondences. This idea has been adopted in stereo [3, 4, 9, 8], but to the best of our knowledge, it has not been used for scene flow. The advantage of such approaches is a fast performance compared to global variational and MRF methods, and a good accuracy compared to purely local methods, since neighboring pixel relations are not ignored completely.

4.3DEEP CNN CLASSIFICATION

Convolutional layer

Convolutional layer performs a convolution operation over the input producing the output of the similar size. The output of the convolutional consists of many feature maps, their number equals the number of filters in the layer. In image processing applications, a 3D convolutional operation is performed – it means that both input and output have 3 dimensions (width, height, number of feature maps). Each convolutional layer is described by the hyperparameters: a size of filter and a number of filters in a layer – those values are chosen by user before the training. Stacked pile of convolutional layers could detect high level features e.g. presence of mouth in the face image.

Nonlinear layer

The nonlinear layer is placed after each convolutional layer. This layer performs some nonlinear function on the output of convolutional layer and increases the approximation abilities of the network. The most widely used nonlinear function in deep learning models is Rectified Linear Unit (ReLU) described by the following formula

$$g(x)=max(0,x)$$

Pooling layer

The convolutional layer or a group of few convolutional layers are often followed by pooling layer. This layer reduces the size of the feature maps. Moreover, pooling layer has generalization abilities and make the representation become invariant to small translation of the input.

Dropout layer

The dropout layer performs inexpensive and powerful operation that highly improve generalization abilities of the neural network.

Fully connected layer

The fully connected layer has its neurons connected to all neurons in the previous layer. These layers are used as a last elements of deep neural classifier, which are feed by the features extracted by the successive convolutional layers. The last layer that produces the output of the network is a softmax layer or sigmoid neuron, depending on the solving task –binary or multiclass classification.

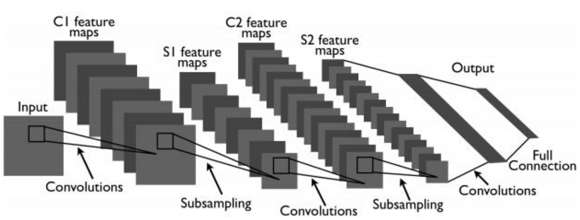

FIGURE 4.1 DEEP CNN CLASSIFICATION

5.EXPERIMENTAL ANALYSIS & RESULTS

Our proposed project will be implemented with windows8 with i5 processor with the help of mat lab 8.4. We have collected the 40 Retinal images stored in our database and trained our database to ready for determine the Diabetic retinopathy accurately. In our preprocessing phase load the test image from a testing database. The preprocessed image is given in the figure 5.1

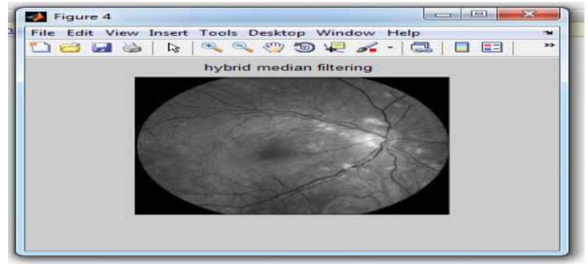

Figure 5.1 Preprocessed Image

In the first phase, image is preprocessed and the preprocessed image is as input for the next phase Seed point construction process. The extracted seed point disparity map and detected area are to be shown in figure figure 5.2 and 5.3

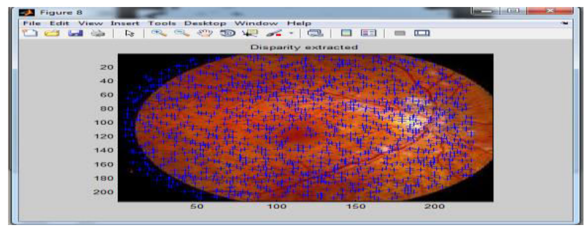

Figure 5.2 Disparity Extracted Image

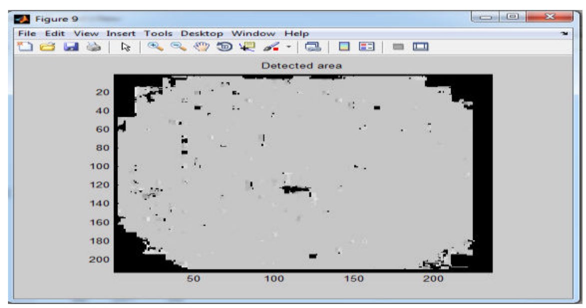

Figure 5.3 Detected Area Image

After the seed point construction process the Deep CNN classifier is used to Classify the disease is shown in figure 5.4.

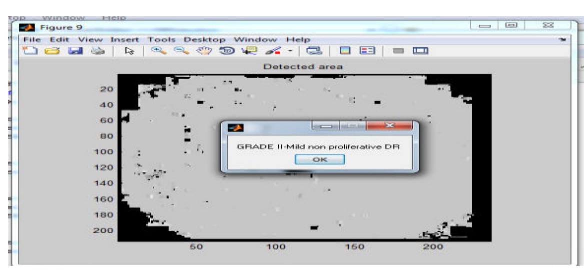

Figure 5.4 Output Image

RESULTS

In our diabetic retinopathy project has used two filters with different algorithm. Hybrid median filter works well better than Gaussian filter and thir flow is given in the figure

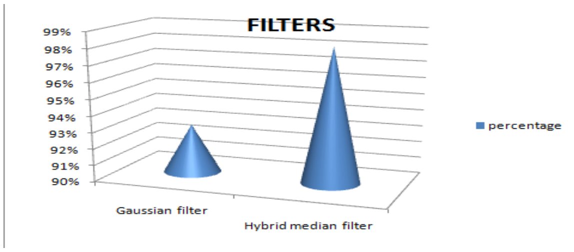

Figure 5.5 Variation Levels In Filters

Few statistical metrics to evaluate classification performance of the tested network. For the binary classification evaluation metrics include: accuracy (ACC), sensitivity (SE), specificity (SP). The metrics are defined as follows:

$(ACC) = TP+TN/(TP+TN+FP+FN)$
$(SE) = TP/P = TP/(TP+FN)$
$(SP) = TN/N = TN/(TN+FP)$

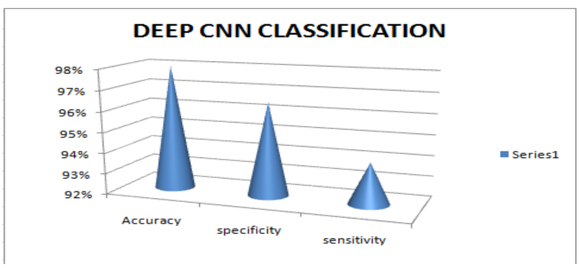

Figure 5.6 Results Of Deep CNN Classification

Evaluation metric comparison of support vector machine and Deep convolutional neural network are represented in the below figures

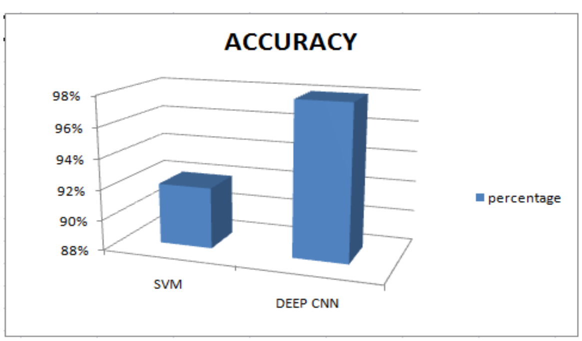

Figure 5.7 Result of Accuracy Comparison

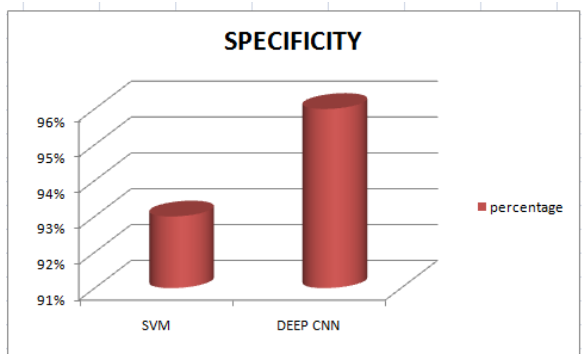

Figure 5.8 Result of Specificity Comparison

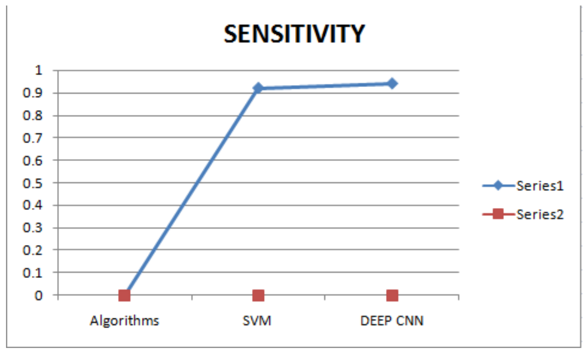

Figure5.9 Result of Sensitivity Comparison

5.CONCLUSION

Detection of diabetic retinopathy in retinal image is a challenging one .So we predict the method for detection in three stages. One is to remove the impurities from the image. Another one is to extract the seed points from the image. Seed points would be really helpful to categorize the disease. In retina the abnormal tissue has to be grown in enormous manner than normal tissue which are categorized under an abnormal image. If the retina contain some normal tissue they are categorized under normal image. Classifying the grading of disease can be done using Deep CNN classification. The experimental results have shown that this technique is robust in detecting and bounding the abnormal cells in retinal images despite in homogeneity intensity or the complicate shape of the diabetic retinopathy.

VI.FUTURE ENHANCEMENTS

In future, we have plans to collect a much cleaner dataset from real UK screening settings. The ongoing developments in CNNs allow much deeper networks which could learn better the intricate features that this network struggled to learn. The results from our network are very promising from an orthodox network topology. Unlike in previous methods, nothing specifically related to the features of our fundus images have been used such as vessels, exudate etc.

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